Remote sensing of diverse urban environments: From the single city to multiple cities

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Abstract

Remote sensing of urban environments has unveiled a significant shift from single-city investigations to the inclusion of multiple cities. Originated from the ideas of the *Remote Sensing of Environment* special issue entitled "Remote Sensing of the Urban Environment: Beyond the Single City," this paper offers a comprehensive examination of the state of the science in multi-city remote sensing, and aims at fostering the rapid advancement of this emerging field to address global sustainability challenges and support knowledge development needed for a new discipline – urban sustainability science (USS). Through a synthesized review of eight key research fields within urban remote sensing [i.e., land use and land cover (LULC) and change, urban vertical structure, urban heat islands, hazards, energy use and emissions, air quality, carbon budgets, and green space], the paper provides insights into the underlying rationale for conducting multi-city studies, the criteria employed in the selection of cities, the societal applications, as well as the opportunities and future directions for expanding the scope of assessments in multi-city remote sensing.

Keywords: Urban, multi-city, remote sensing, synthesized review, future direction, urban sustainability science

1. Introduction

Over the past two decades, the conceptualization of urban areas has evolved from one primarily focused on localism to one that acknowledges the global reach of urban areas. Urban areas are now commonly considered nodes in a highly interconnected global network (Sassen et al., 2004; Brenner et al., 2006). They are global in their demands on the environment, e.g., how they source their resources and expel their waste, propagating changes in distant teleconnected landscapes (Seto et al., 2012; Meyfroidt et al., 2022; Wiedmann et al., 2018). They are also global in that they, collectively, play an out-sized role in determining the future of many of the planet's largest sustainability challenges. Cities are responsible for the majority of CO_2 emissions, and increasingly are recognized for their sizeable fugitive methane emissions (de Foy et al., 2023), but also have an opportunity to accelerate systemic climate responses. A recent Intergovernmental Panel on Climate Change (IPCC) special report on cities emphasizes that urban climate change mitigation will determine the future of the global climate (IPCC, 2022). In addition, the social, economic, and political power to address global sustainability challenges like climate change and inequality are based in cities.

We argue that this increasing urban ambit over global sustainability necessitates a shift in how urban areas are studied. Whereas historically scientific inquiry focused on the uniqueness of individual cities, the pace of urbanization, and the urgency of Earth's current environmental crisis requires a parallel urban science that can scale up to meet the demands of global sustainability challenges. For the field of urban remote sensing, this means generating an integrated understanding of an urbanizing planet and helping build the science of what makes urban areas sustainable, both of which require more multi-city studies. Here, we define ‘multi-city remote sensing’ to be studies that span two or more cities of diverse geographical patterns and can advance the understanding of urban systems at the regional or global scale with highly generalizable knowledge or insights. With the swift progress in remote sensing technology, we note that the term 'multi-city' has evolved from initially involving a small number of cities (e.g., two to three) to now encompassing dozens or even hundreds/thousands of cities. Studies of a small number of cities sometimes represent a more targeted test of specific hypotheses or they were used to apply ‘experimental control’ to some variables, e.g., choosing two cities similar in all respects except for a characteristic under study. Here, we include publications that considered more than one city for the analysis in this review.

In this study, we aim to summarize the current state of the science in regards to multi-city remote sensing. We provide insights into why multi-city studies are important, when and why they are usually performed, and future opportunities for growing the number of multi-city remote sensing assessments.

Our work originated from the special issue 'Remote Sensing of the Urban Environment: Beyond the Single City' published in the journal *Remote Sensing of Environment*, but offers a more in-depth perspective on multi-city remote sensing to promote the rapid growth in this emerging field.

2. The shift from single- to multi-city remote sensing in urban studies

Urban remote sensing analyses remain limited in scope, often focusing on a single city. In a recent meta-analysis of 644 urban remote sensing papers from 1980 to 2020, 79% focused on a single urban area or agglomeration (Reba et al., 2020). While case studies are often necessary to connect remote sensing data to in-depth insights from fieldwork, single city studies are limited in their ability to point out patterns and variations in patterns, to contribute to theory or enhance generalization, and to produce knowledge that may be transferred and applied elsewhere.

In contrast, urban remote sensing studies that include multiple cities are important for several reasons: (i) Comparative analysis or common patterns and processes: By studying multiple cities, researchers can make comparative analyses of the urban environment, such as land patterns (Schneider and Woodcock, 2008; Güneralp et al., 2020), structural change (Frolking et al., 2013, Mahtta et al., 2019), and infrastructural investment (Stokes and Seto, 2019), based on different cohorts (e.g. region, climate zone, city size, stage of development). These comparisons can help to identify patterns and trends that may be unique to a particular area, as well as highlight similarities between different regions. (ii) Cumulative impacts: Urban remote sensing of multiple cities can help identify the cumulative impact of urbanization. Impacts that are not apparent at a smaller scale, can be revealed when looking across multiple cities. Understanding the cumulative impact of cities is necessary to link urban processes to planetary health. (iii) Policy development or generalizable insights: Urban remote sensing studies can help inform policy development by providing policymakers with data on urban growth and development and physical changes to the urban environment. By studying multiple cities, policymakers can better understand the factors that contribute to successful urban planning and development, as well as the challenges that cities face in terms of sustainability, environmental management and quality of life (Huang and Liu, 2022). Instead of examining multiple cities within a single framework, an alternative approach involves conducting separate single-city studies and subsequently analyzing and comparing their findings. However, it is important to acknowledge that variations in data quality, remote sensing algorithm or its parameters, and the evaluation criteria of algorithm's performance among these studies are likely to introduce significantly higher uncertainties compared to those encompassing multiple cities in a consistent system.

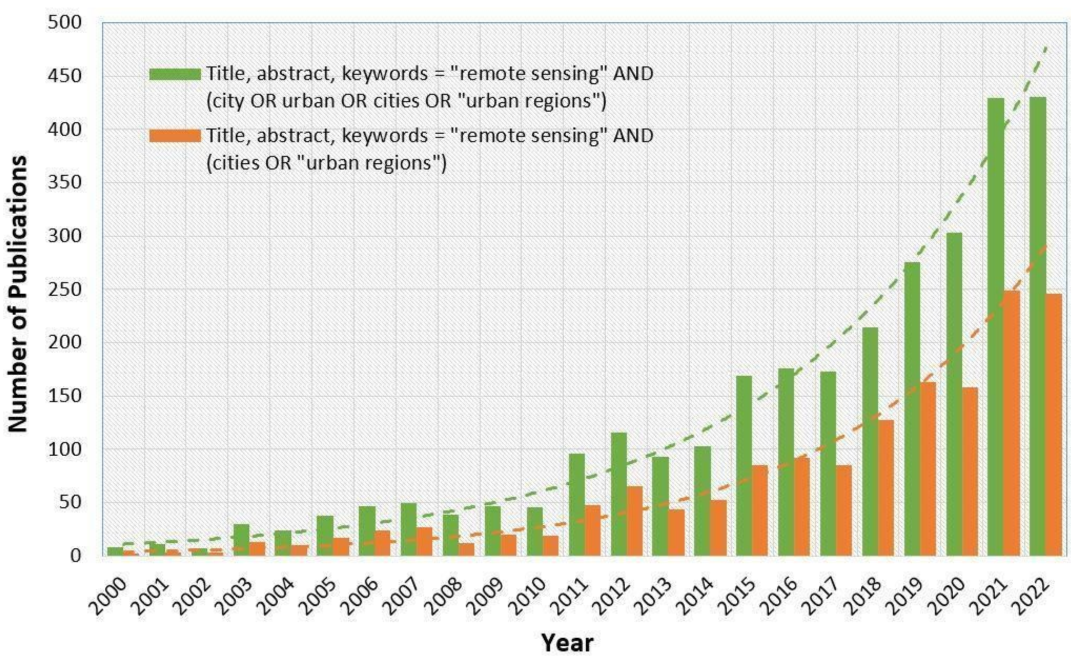

Fig. 1. Comparison of the number of remote sensing publications discussing single or multiple cities (green bars) versus those discussing multiple cities only (orange bars) from 2000 to 2022.

The past decades, particularly since 2000, have witnessed an explosive growth of studies in urban remote sensing. Using the popular ScienceDirect© database, we conducted multiple searches to assess the number of journal articles published in urban remote sensing over the years and evaluated the geographic distribution of the studied cities. We first compared the number of publications discussing single or multiple cities versus those discussing multiple cities using the formula in Fig. 1. We limited the search to title, abstract and keywords, which ensured a 'remote sensing' and 'urban' emphasis in the search results. Both types of studies show a substantial increase over the past two decades with similar exponential trends (Fig. 1). The number of publications grew from fewer than 10 per year in 2000 to over 400 and 200 per year by 2022 for remote sensing studies focusing on urban/city and multiple cities/urban regions respectively. We note that research focusing on a single city study site may contain descriptive language about 'cities' or 'urban regions' in the abstract, and the number for multi-city studies is likely overestimated in Fig. 1. However, the overall trend suggests researchers' increasing interest in broadening urban case studies. Geographically, the majority of the multi-city studies were focused on large cities in China, Europe, and North America. We expanded the aforementioned multi-city formula by further including *AND China*, *AND (Europe OR United Kingdom OR Germany OR France OR Netherlands OR Spain)*, and *AND ("United States" OR USA OR U.S. OR Canada OR "North America")* for the three geographic regions, respectively. Results show a similar number of studies from Europe versus those from North America, which have steadily increased from less than five in 2000 to almost 20 per year more recently (Fig. 2). Remote sensing studies on Chinese cities also showed an upward trend in the past two decades, but at a faster rate. Chinese studies made a substantial contribution to the explosive increase of urban remote sensing publications. Their number of publications in 2022 is more than twice that of the studies of North American and European cities combined (Fig. 2).

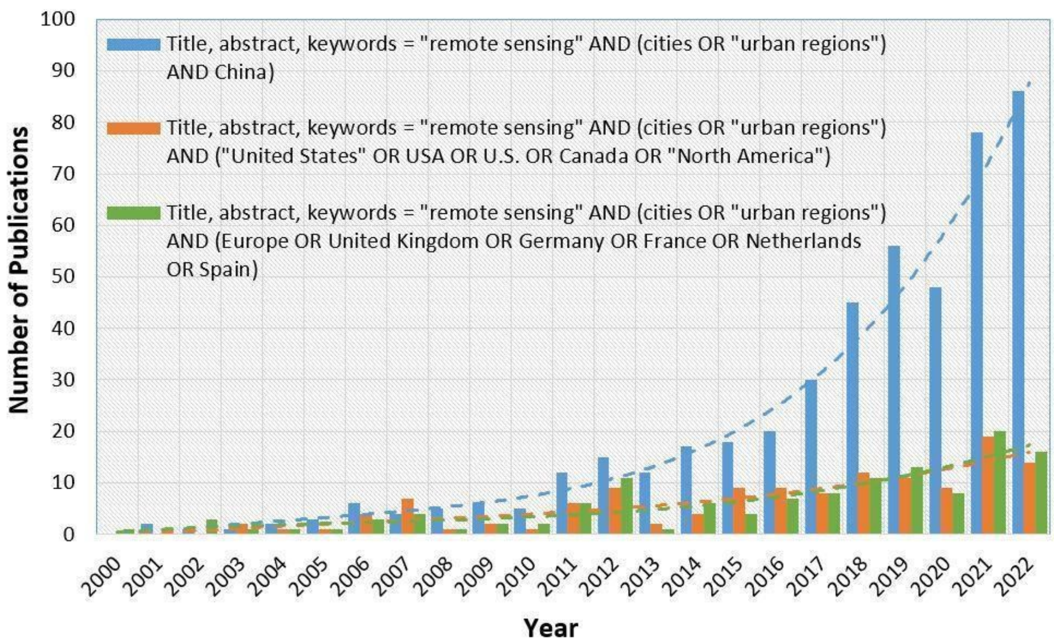

Fig. 2. Comparison of the number of remote sensing publications for multi-city studies in China (blue bars), North America (orange bars) and Europe (green bars), from 2000 to 2022.

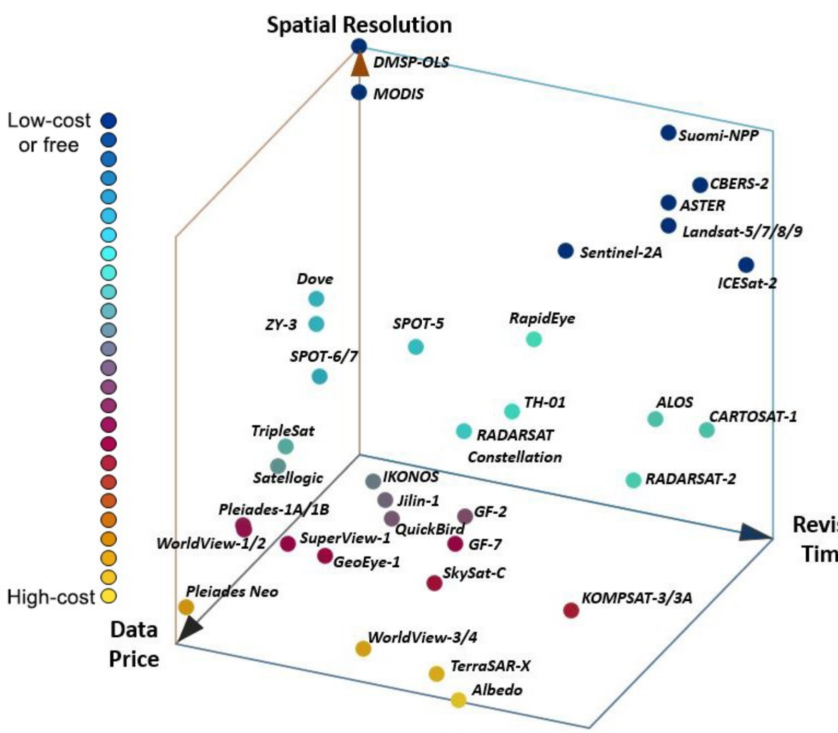

Fig. 3. A 3D cube with axes of spatial resolution (fine to coarse), data price (low to high) and revisit time (short to long), which includes 35 sample satellite sensors for multi-city studies. The blue-to-yellow color scheme shows the increase of data price from low/free to high.

The development of new remote sensing satellite systems has also helped to increase the number of multi-city studies. The trends of higher spatial resolution (to capture various degrees of heterogeneity), cheaper data acquisition costs, and shorter revisit time for state-of-the-art satellite sensors have become a game changer by offering urban researchers high flexibility to study or compare urban regions of diverse geographic characteristics. Fig. 3 includes 33 satellite sensors that have been used in multi-city studies distributed in a 3D cube with axes of spatial resolution (fine to coarse), data price (low to high) and revisit time (short to long). We used a blue-to-yellow color scheme to show the differences in data price from low/free to high. While high or very high spatial resolution data (finer than 5 m) remains costly, the associated sensors have a much shorter revisit time than their predecessors (e.g., 1.1 days WorldView-2 versus 16 days Landsat-8), because they are flown in a constellation. The short revisit time facilitates rapid monitoring of and responses to urban changes. A number of sensors are now offering free data access with resolutions suitable for numerous aspects of the urban studies (e.g., global impervious surface mapping with 10 m resolution Sentinel-2 imagery; Sun et al., 2022).

It is important to note that more data points will not necessarily advance insights into how urban systems work or lead to better decision-making. As with all sciences, the sample is important. Cities in multiple city studies need to be selected so that insights can be created that can be extrapolated beyond the cities in the study. For example, there is a documented gap in geographic coverage of low and lower-middle income countries in urban remote sensing, as well as an overfocus on megacities, where only 11% of the world's urban population resides (Reba and Seto, 2020). More multi-city studies that focus on Chinese, European or North American megacities will not help to build insights about the small and medium sized towns of the Global South where most future urban growth will occur.

3. Multi-city remote sensing: development, rationale, societal impact, and challenges

Remote sensing contributes to sustainable urban development from a variety of perspectives. Here, we provide a synthesized review of representative urban remote sensing topics that have traditionally or recently captured the attention of urban researchers and practitioners, including land use and land cover (LULC) and change, urban vertical structure, urban heat islands, hazards, energy use and emissions, air quality, carbon budgets, and green space. The review of each topic was performed from the multi-city angle, where we would like to answer the following questions: (i) What was the rationale for multi-city studies? (ii) How were the studied cities chosen and how were they distributed geographically? (iii) What was the societal impact of those multi-city studies? And (iv) what challenges or gaps remain to be addressed?

3.1. Land use and land cover (LULC) and change

LULC assessment has long been an integral part of multi-city studies. Accurately identifying changes in urban LULC can provide valuable insights into the drivers and socioeconomic effects of urbanization. Here, studies over the past decade were retrieved using “land cover”, “land use”, and “multi-city” as the keyword, with single city studies and articles not based on a remote sensing method excluded. The majority of studies on multi-city LULC have focused on a regional scale, with only a few studies examining a number of megacities across the globe.

The rationales for multi-city LULC studies are multifaceted, as they often intersect with other research fields. Both generalizability and representativeness are important rationales for multi-city LULC studies, which are associated with the study's scale and objective. Here, generalizability and transferability were considered interchangeable as the diverse landscapes in multiple cities can improve the ability of the developed model to adapt to new, previously unseen urban environments. Regional-scale studies mostly selected major cities covering large administrative regions (Srivastava et al., 2019), such as the 23 cities in the Changsha–Zhuzhou–Xiangtan region (Fan et al., 2022; Liu et al., 2020), and three metropolitan areas in China (Li et al., 2020b). On the other hand, studies on a larger scale, such as a national to a global scale, tended to place a greater emphasis on representativeness (Angel et al., 2011; Chi et al., 2015; Huang et al., 2020; Huang et al., 2021). Furthermore, the objective of the study can also influence the rationale in multi-city LULC studies. For instance, the high variation in the severity of air pollution was one of the primary drivers for studies that integrate land use and air pollution across cities (Han et al., 2021).

The selection of cities in multi-city LULC studies was primarily based on their regional or global significance or rapid urban expansion. For instance, in regional-scale studies concerning urban sustainability, the importance of cities, as measured by factors such as population and economic status, is a primary criterion (Fekete & Priesmeier, 2021; Ju et al., 2022; Liu et al., 2020; Yue et al., 2019). The rate of urban expansion is another commonly used criterion (Koroso et al., 2020; Yao et al., 2022). Furthermore, in papers that focus on method development, the selection of cities is often more concerned with the availability of data for validation purposes (Bousbih et al., 2022).

At all scales of multi-city LULC studies, remote sensing plays an important role in identifying representative and universal drivers of land use changes (Gutman et al., 2008; Karra et al., 2021; Yang and Huang, 2021; Zhang et al., 2022b). Changes due to urban LULC at the parcel level, such as the expansion of impervious surface areas, taller buildings, and the creation of green spaces, can have substantial environmental implications. For example, a reduction in grasslands and an expansion of urban areas have resulted in carbon losses and water quality deterioration (Lai et al., 2016; Liu et al., 2019; Teixeira et al., 2014). Furthermore, the varying climatic backgrounds across different cities have led to differences in the impact of land cover on the urban thermal environment (Masoudi et al., 2019; Wang et al., 2020). Nonetheless, certain limitations, such as data availability, quality, and comparability across different regions or time periods remain to be addressed (Wu et al., 2019).

3.2. Urban vertical structure

Urban vertical structure estimation aims to expand our ability to capture and analyze urban spatial heterogeneity from horizontal land cover to its vertical structure. Urban areas have been intensively mapped in 2D while their vertical dimension is drawing increasing attention due to its important contribution to understanding urban ecosystem functioning, such as population distribution, energy use, and economic growth (Koziatek & Dragićević, 2017; Zhou et al., 2022). This section focuses on the extraction of urban vertical structure, due to its pivotal role in 3D mapping and its prevalence in recent multi-city studies.

Compared to land cover, urban vertical structure often exhibits greater variance. Densely inhabited cities tend to have taller buildings (e.g., more skyscrapers) and rougher surfaces than those less populated (Barr and Luo, 2021). From the perspective of geomatics or civil engineering, efforts have been devoted to reconstructing or simulating urban environments at a fine scale (e.g., individual building or tree level), while developing models (or software products) that are (semi-)automatic or more ideally end-to-end to improve efficiency and reduce costs. Multiple cities are needed for model calibration or validation to meet user needs over diverse urban regions. Since the 2010s, there have been tremendous efforts to develop benchmark datasets that can serve as a baseline for assessing models' generalization ability in 3D mapping. A notable example is the International Society for Photogrammetry and Remote Sensing (ISPRS) 3D Building Reconstruction benchmark providing building roof 3D structures in two cities, Vaihingen, Germany and Toronto, Canada (Rottensteiner et al., 2014). One recent trend is the adoption of machine learning (ML), particularly deep learning (DL) in vertical structure estimation (e.g., Cao and Huang, 2021; Yan and Huang, 2022). Because deep neural networks have a large number of parameters, a key to strong model generalization ability is feeding the model with massive amounts of training data that represent various types of urban environments. In an effort to extract building height over 42 Chinese cities, Cao and Huang (2021) used buildings located in 4,723 sample grids (1x1 km each) from an existing dataset across the studied cities. From the perspective of sustainable development, multi-city studies or intra-city comparisons can expand our ability to discover the patterns or underlying mechanisms of urban system functioning across cities at the regional to global scale. For example, Pérez-Urrestarazu et al. (2016) systematically reviewed and analyzed the ecological, environmental and social impact of vertical greening systems (vegetation to spread over building facades or interior walls) on the sustainability of densely built urban areas. Zhou et al. (2022) discovered that urban built-up heights are significantly correlated with inequality in the Global South by examining global cities in 159 countries.

The majority of urban vertical structure studies have focused on large cities, especially those in countries or regions of strong economic development, such as Europe, China and the U.S. The rationale for selecting specific cities was vague or not mentioned in most studies. Those that did mention the criteria often provided a qualitative description, including phrases like “diverse buildings” or “representative urban structures” (e.g., Cao and Huang, 2021; Tan et al., 2022). While not explicitly discussed, data availability may have also affected the geographic distribution of those studies. Different from classic land cover mapping, developing a 3D model requires the vertical information of urban structure as input, which is labor intensive and costly to collect. However, recent attempts have demonstrated the potential to address this challenge by applying street view images to efficiently and accurately estimate building/tree height or street canyons (e.g., Li et al., 2018; He and Li, 2021).

Urban vertical structure datasets serve as a foundation to support a range of societal applications across cities, including urban heat island effects (Berger et al., 2017), urban energy use (Li et al., 2017), urban nighttime image analysis (Tan et al., 2022), heritage recording (Remondino, 2011), air pollution dispersal (Yang et al., 2020), population distribution (Biljecki et al., 2016), inequities (Zhou et al., 2022), and economic growth or GDP (Frolking et al., 2022). They are also key to implementing “digital twins”, which aim to simulate the urban environment and tackle complex urban challenges in an immersive 3D environment (Dembski et al., 2020).

Urban vertical structure estimation has revealed a promising trend of expanding from single cities to multiple cities. This observation holds especially true with the growing accessibility of very-high-resolution imagery obtained from satellites or Unmanned Aircraft Systems (UAS), coupled with advanced modeling and computer vision approaches. However, when it comes to large area coverage, the spatial resolution of most products remains comparatively low. This may have restricted many building-level applications to 'case studies' over one or a limited number of cities. With the increasing availability of urban vertical structure data, the maturity of the modeling algorithms, and the advance of computing power, fine-scale 3D models are expected to be widely available in a multi-city setting. In comparison to mapping the outdoor environments, extracting the inner 3D structure of the buildings (i.e., indoor mapping) has received increasing attention more recently. However, the indoor environment is even more complex. Particularly, intensive manual intervention is required in indoor mapping, which makes city-scale or cross-city mapping a challenging task (Ying et al., 2020).

3.3. Surface urban heat island

The surface urban heat island (SUHI) has long been a target of multi-city studies as researchers seek to characterize the spatiotemporal behavior of the SUHI and to relate its characteristics to various influencing factors. Up to about 2010, most studies focused on individual cities (Zhou et al. 2019); in the period since 2018 we identified approximately 150 multi-city studies. Just over half focus on a select country, with smaller but similar percentages (12-16%) that identify a global, continental/regional and sub-national scale as the focus.

The rationale for these studies is most often 'generalizability' or 'representativity'. Representativity focused studies often use a small number of cities, magnifying the importance of selection criteria. Around 15% of studies self-characterize as 'comprehensive' – often (but not exclusively) associated with global or national scale assessments with large numbers of cities. Some comprehensive studies target a smaller geographic scale and restrictive selection criteria, e.g., all megacities within a particular nation. Study rationales also include: methodological assessments, specific tests or comparisons, or a more general 'characterization' of conditions. Multi-city studies incorporate anywhere from 2 to over 10,798 cities (She et al., 2022). Over 50% of studies used more than 50 cities, and more than 10% processed more than 1000 cities. Sample size is associated with spatial scale of the study: the very largest studies are typically global scale, with a few national (China and USA) scale studies. Some recent articles assess urbanization with respect to impervious surface cover rather than providing a distinct city 'count' (Sismanidis et al., 2022; Zhou et al. 2022).

Selection of cities use a variety of criteria with population and climate zone most frequently noted. Physiographic setting, city political, socioeconomic and/or cultural importance and urban area were also frequently used. The availability of ancillary data has become more important for studies that seek to better understand the mechanisms associated with the SUHI and its interaction with other aspects of the urban environment. Some examples include: relations between SUHI and the canopy air temperature heat island (e.g., Du et al., 2021; Hu et al., 2019; Venter et al., 2021), linkages between air quality and the heat island (e.g., Han et al. 2020), the influence of anthropogenic heat (e.g., Jin et al., 2020; see also Section 3.5), and meteorological controls on the heat island (Lai et al., 2021). Applying multiple criteria was common and, in such instances, criteria were often applied sequentially – e.g., cities were first selected on the basis of area and/or population and then further categorized by climate zone. A number of studies target all cities at a particular scale of a given size (population or area).

Three regional science and societal application themes arise. First is the use of multi-city studies to advance our understanding of SUHI formation and evolution, either holistically or in relation to influencing factors, especially the background climate (and associated biome), but also urban form (e.g.

Stuhlmacher et al., 2022), structure (Cao et al., 2022) and vegetation (Chakraborty and Lee, 2019). Other factors include energy use and human activity modifications, for example COVID-related shutdowns (e.g. Alqasemi et al., 2021; Liu et al., 2022) or how the SUHI is related to socioeconomic conditions (Chakraborty et al., 2019). Second is methodological advances in how multi-city SUHI are studied, e.g., use of Local Climate Zones (Bechtel et al., 2019), or how 'urban' is defined (Chakraborty et al., 2020; Zhou et al., 2022). These methodological advances are intended to provide more consistent approaches for identifying urban areas to allow more comprehensive understanding of the SUHI and overcome limitations that may exclude smaller and/or less urbanized regions. A third theme is information to help guide heat mitigation and adaptation strategies and urban planning policies. While some studies provide specific advice, usually linked to climate region or climate parameters, many papers are generic in their guidance, not surprising given a common focus is often the identification of SUHI spatiotemporal variations. Application of findings to SUHI mitigation must be considered with caution because the heat island intensity is highly dependent on the reference non-urban conditions and the intended target of most heat mitigation is canopy layer air temperatures or heat stress (Sismanidis et al., 2022; Martilli et al., 2020).

Multi-city SUHI studies must continue to incorporate ground-based in-situ measurements, particularly air temperature, but also air quality and surface energy balance parameters, synchronous with remote observations, to advance a more holistic understanding of the urban physical environment. Incorporating more physical factors that affect the spatiotemporal characteristics of urban (and rural) surface temperature into the analysis is needed; e.g. building height or 3D structure; socioeconomic information; vegetation details; air quality; and energy consumption. Some of these (3D structure) pose a challenge for large scale studies (Liu et al., 2021) that may demand higher resolution satellite imagery with global coverage. Others, such as socioeconomic and energy consumption data are complicated by jurisdictional differences that can limit multi-scale and multi-city analysis. Combining satellite remote sensing with numerical modeling of surface and canopy layer air temperatures is also important for multi-city studies to broaden physical process understanding. Finally, in the quest to determine cumulative impacts and to provide policy relevant information, it is necessary for multi-city studies to take on the challenge of assessing urban heat mitigation strategies, especially at the intra-urban scale, while remembering that the surface temperature observed is both an incomplete representation of the full urban surface and is different from urban air temperature – the focus of much urban climate adaptation efforts.

3.4. Urban hazards

Satellite remote sensing is an important tool for assessment of hazards and the damage that arises from particular events. Here we examine multi-city studies reported for four categories of hazards: ground movements (such as earthquakes and landslides), damage assessment, flooding, and heat waves. Air quality is covered separately in section 3.6.

3.4.1. Ground movements

Raspini et al. (2022) in their review of satellite radar interferometry used to study ground-movements arising from earthquakes or landslides showed the vast majority of studies that involve cities are case-study based. Recent advances afforded by the global coverage of Sentinel-1 has made possible investigations over larger regions that include multiple cities. Del Soldato et al. (2019) provided an example of a regional scale monitoring system using satellite interferometric data. The regional scale incorporates a range of urban settlement sizes and provides the ability to detect temporal changes related to slow-moving landslides and subsidence. Bianchini et al. (2021) used multi-temporal satellite interferometry as part of an integrated system that incorporates ground-based instruments for landslide management and mitigation strategies over the region. Crosetto et al. (2020) described ground motion services at national and continental scales for Europe that have many urban applications. Confuorto et al.

(2021) determined a greater frequency of detected anomalies over urban areas in Tuscany, Italy relative to other study areas, helping identify risks to urban environment.

3.4.2. Damage assessments

At fine spatial scales, remote sensing can contribute to assessment of damage arising due to earthquakes or conflict in urban areas. Damage from earthquakes in urban settings is often largely a case-based type assessment (Cooner et al. 2016), but multiple cities may be used as part of training for algorithms that assess destruction detection (Ali et al., 2020) wherein developing transferrable models requires a large dataset of labeled buildings that cover different building types (Matin and Pradan, 2021). Night time light (NTL) analysis also provides an ability to assess earthquake-impacted areas at regional scales (Levin, 2023). Speed of assessment is critical to this application given the need for emergency response. Recovery monitoring is also relevant. There is a need to overcome the manual (and slow) visual interpretation of images, especially for fine scale assessments.

Cities and urban infrastructure are often a focus of remote sensing monitoring for conflict impacts (Van Den Hoek, 2021; Kaplan et al., 2022). Geographic study areas are often regional or national in scope and thus the multi-city context is often implicit. Jiang et al. (2017) undertook an analysis of multiple cities in Syria and Yemen respectively using NTL. This allows national scale assessment as well as the ability to compare impacts between cities. Mueller et al. (2021) showed the application of an automated method for assessing building destruction for major cities in Syria where multiple sites are used to demonstrate the generalizability of the method. Their work advances the ability to detect building destruction and identifies that a strong reliance remains on human interpretation, especially at the building scale. Zhang et al. (2020) used NTL for assessing the crisis in Venezuela between 2012-2018 that incorporated a multi-city component used to help track migration of residents from urban centers to suburbs that again targeted regional to national scales but which enables comparisons between cities. The need for multi-city study is implicit in Bennett et al.'s (2022) recommendation of the need to produce analysis-ready, conflict-wide very high resolution remotely sensed imagery mosaics to harmonize monitoring.

3.4.3. Flooding

Remote sensing using synthetic aperture radar (SAR) has mapped flooding in urban areas but methods and applications intended for assessing flooding urban areas have been less frequently examined (Zhao et al., 2022). More generally, flood mapping in urban areas is challenging due to the built structure (e.g. Schumann et al., 2022). Multi-city studies are valuable for providing training data for ML/DL methods, but getting appropriate training data is difficult. Zhao et al. (2022) examined six different urban flood cases from four study sites; their multi-city approach is based on the occurrence of the event and a desire for generalizability of their method. As with other hazard events, single city case studies are important for methodological development and testing. The choice of sites relates to the need for other datasets, the event itself, and an assessment of the performance of their method at a river confluence – i.e., physical geographic setting was a consideration (Mason et al., 2021).

3.4.4. Heatwaves

Heatwaves are an important urban hazard that is often represented as a motivation in SUHI studies. Satellite-derived urban surface temperature is often used as a proxy to assess urban heat stress during heat waves but Chakraborty et al. (2022) showed that spatial variability of heat stress is not well captured by these observations. Their results imply that caution must be used in the use of remotely sensed surface temperature to guide heat mitigation in cities (see also the cautions in the SUHI section). Their use of European cities was targeted to provide a broad range of cities for representativity, but their limited range of climates motivates work for cities in arid and humid regions.

Keramitsoglou et al. (2016) provided an example of an explicit multi-city study that focused on heatwave identification and reducing its risks in urban areas. They examined multiple cities in Europe and North Africa to assess a geostationary satellite-based method to monitor air temperature in real time.

The multi-city application was intended to serve a range of end users of the data and the evaluation used 15 cities so as to provide variety in environmental conditions, with explicit recognition of different climate zones. The selection of cities allowed performance variations dependent on city topographic setting to be diagnosed, along with diurnal variations in performance. The multi-city approach enables a broader application of the data including heatwave monitoring and energy demand and to allow its interface with other local and regional data sources.

3.4.5. Summary of urban hazards

As might be anticipated, many urban hazards studies relate to a single city or small regions linked to a particular hazard, e.g. hurricane damage assessments (Al-Amin Hoque et al., 2017) or to methodological development. Multi-city studies are often implicit rather than explicit through coordination at larger scales. Generalizability, e.g., for training of algorithms, was noted for a number of studies. Multi-city studies also broaden the area assessed, serve more end-users, and allow comparison of impacts between cities, even if the multi-city aspect was initially unintentional. Hazard occurrence is the main driver of how studied cities were chosen for post-event type studies, with the need to link to other datasets, and background climate/physiographic setting also influencing city choice. Societal impact comes from the ability of multi-city remote sensing to provide rapid and effective disaster response and recovery assessment. More broadly, multi-city hazard studies contribute to building resilience through understanding impacts of past events and for developing mitigation strategies and forecasting/warning systems, e.g., for heatwaves. Looking forward, some general challenges relate to the need for sufficient spatial resolution (or downscaling techniques) to match the scale of the hazard assessment being undertaken, rapid revisit time and freely available data (Poursanidis and Chrysoulakis, 2017). Complementary high-performance computing or use of cloud-based services is needed to provide the fast analysis required to be relevant for operational response to hazard occurrence. Methodological developments to reduce reliance on human interpretation (e.g., for building-scale damage assessments) and to better relate satellite derived quantities to the relevant hazard (e.g., directional brightness temperature vs urban canopy layer heat) are also needed.

3.5. Energy use and emissions

The discharge of energy caused by human activities can have a significant effect on the surface energy balance in urban environments (Zhou et al., 2012). Remote sensing techniques have enabled a better understanding of human impacts on the urban environment by providing wider geographical coverage and finer spatial detail of energy use and heat emissions caused by human activities (Yu et al., 2021b). Combining multi-source remote sensing data with inventory-based anthropogenic heat emission (AHE) and energy use methods offers significant advantages in estimating AHE and energy consumption at a large scale (Sailor and Lu, 2004), which has enabled the comparison between multiple cities, facilitating an improved understanding of human impacts on urban environments of varying backgrounds of climate (Chrysoulakis et al., 2016), population density (Cao et al., 2014), and socioeconomic status (Yue et al., 2019).

Most multi-city energy use and emission studies were motivated by the need to develop new methodologies. There is a growing need for global and national estimates of AHE and energy use in order to better understand human impacts on the urban environment (Chen et al., 2020). Several studies on AHE have used data from multiple remote sensing sources, including LULC, DMSP/OLS NTL, Normalized Difference Vegetation Index (NDVI), land surface temperature, and global urban footprint, in combination with population density data (He et al., 2020), road network data (Qian et al., 2022), point-of-interest data (Wang et al., 2022b), or urban building characteristics (Yu et al., 2021a), to improve AHE mapping and investigate spatial variations across multiple cities with diverse socioeconomic backgrounds (Chen et al., 2012; Yang et al., 2014). Many energy use studies have chosen to use the total brightness of NTL imagery as a key indicator to examine the distribution of electricity consumption in cities around the world, such as Australia (Townsend and Bruce, 2010), China (Cao et al., 2014; He et al., 2012; Shi et al., 2014; Zhao et al., 2012), and globally (Shi et al., 2016; Xie and Weng, 2016).

In many multi-city energy use and emission studies, city selection was primarily based on factors such as the cities' significance or their climate background. For instance, metropolitan areas (e.g., Beijing, Shanghai) and urban agglomeration areas (e.g., Pearl River Delta, Yangtze River Delta) in China were frequently chosen (e.g., Chen et al., 2020; Qian et al., 2022). These cities were compared in detail in terms of their AHE and electricity consumption over a long time period. In Europe, city selections were often based on the climate background of the city. For instance, in the URBan Anthropogenic heat FLUX from Earth observation Satellites (URBANFLUXES) project, three distinct European cities situated in different climate zones were selected (Chrysoulakis et al., 2016).

The enhanced estimates of energy consumption and emissions in multi-city studies can help to reveal diverse spatial patterns of electricity energy consumption and better understand the impact of human activities on urban thermal environments. Incorporating regional AHE profiles into numerical modeling systems has enabled researchers to better understand the significance of AHE in urban energy balance (Sailor et al., 2015), as well as estimate its potential impacts on urban climate and air quality. Due to a lack of data on AHE, urban modelers are often forced to either turn AHE off or use representative profiles that do not account for spatial variations in AHE within the city (Block et al., 2004; Dokukin and Ginzburg, 2020; Gabey et al., 2019). Remote sensing data has facilitated the development of regional AHE datasets, which have been incorporated into the Weather Research and Forecasting (WRF) model to investigate the impact of AHE on urban meteorology and air quality in multiple cities across the Yangtze River Delta region of China (Xie et al., 2016).

3.6. Air quality

Air pollution has become a worldwide concern due to its impacts on human health, weather, and climate (e.g., Anenberg et al., 2022; de Sario et al., 2013). Monitoring the spatiotemporal variations of gaseous pollutants is important to assess air quality and health risks for developing mitigation policies (e.g., Peng et al., 2016; Song et al., 2019). In recent years, air quality has been a growing target of multi-city studies due to rapid urbanization. For example, Anenberg et al. (2019) estimated fine particulate matter PM2.5 mortality in 250 most populous cities worldwide. Southerland et al. (2022) used the Global Human Settlement Grid to identify 13,160 urban areas with population more than 50,000 and a global PM2.5 dataset that combines satellite-retrieved aerosol optical depth, with models and ground observations for a 20-year analysis to demonstrate that most of the world's urban population lives in areas with unhealthy levels of PM2.5. The COVID-19 lockdown periods provided a unique opportunity to assess air pollution in response to changes in human activity patterns. Cooper et al. (2022) assessed the ambient NO_2 changes in 215 global cities during the COVID-19 lockdowns and found that the sensitivity of NO_2 to lockdowns varies by country and emissions sector, demonstrating the critical need for spatially resolved observational information provided by satellite-derived surface concentration estimates. Adam et al. (2021) also provides a critical review on air quality changes in cities during the COVID-19 lockdowns. Here, we focused journal articles on air quality studies using remote sensing data with single city studies excluded.

The rationale for conducting multi-city studies of air quality primarily revolves around three aspects. First, there is a critical need to explore the spatiotemporal variations of air pollutants in the context of urbanization and urban expansion recognizing that cities are important sites of air pollutant emissions and processes and not all cities are well characterized by ground-based observing systems (Li and Huang, 2020). The sources of air pollutants comprise both anthropogenic emissions from industrial production, transportation exhausts, and emissions related to building heating and cooling as well as natural factors, such as wildfires and dust storms (Wei et al., 2023). Anthropogenic emissions have gained increasing attention, particularly in developing countries' cities, due to rapid urbanization accompanied by economic development (Kumar et al., 2020; Zhang et al., 2022c). Park et al. (2021) found that cities show distinct emission patterns according to their geographic location. Second, the availability of remote sensing data provides the possibility to study intra-city and inter-city air quality conditions for improved policy-making (e.g., Wei et al. 2021). Satellite derived emissions are able to provide independent information to verify bottom-up emission estimates and to assess the effectiveness of emission control measures, especially for locations that lack surface observation networks and/or do not have detailed emission inventories. Multi-city studies have benefited significantly from remote-sensing-based long-term and gapless air pollution datasets (e.g., Peng et al., 2016; van Donkelaar et al., 2016; Wei et al., 2022, 2023), with high temporal frequency and spatial continuity characteristics. Third, gathering information on air quality across multiple cities offers the potential to discern general patterns of cities with distinct characteristics at regional or global scales. For example, during the COVID-19 lockdowns, improvements in air quality with reduced concentrations of air pollutants such as NO_2, PM2.5, CO, and SO_2 have been observed in many global cities, but with high variations across cities (e.g., Cooper et al., 2022; Sannigrahi et al., 2021).

Cities included in multi-city air pollution studies were chosen based on various factors, such as known high levels of air pollution (Sannigrahi et al., 2021; Song et al., 2019), large population size (Anenberg et al., 2019), and significance of the city, including metropolitan or provincial capital status, with different climate characteristics (e.g., Ali et al., 2021; Pei et al., 2020). Some assessments required the studied cities to provide a strong contrast of the urban source from its background and in some cases have a homogeneous wind field free from topographic influences (e.g., Lu et al. 2015, Goldberg et al. 2019). Additionally, some studies selected cities as representative samples from different regions or categories for generalizability (Cooper et al., 2022; Vadrevu et al., 2020).

Research on air quality monitoring and assessment across multiple cities can be instrumental in the development of mitigation policies for air pollution. By integrating remote sensing and socio-economic and health data, multi-city air quality studies have the potential to enhance our understanding of air pollutant exposure and associated health risks (Song et al., 2019; Southerland et al., 2022). Multi-city studies have revealed that the sources of air pollutants differ across cities worldwide through various transport pathways (Duncan et al., 2016). Excessive urban expansion has been found to exacerbate air pollution in local cities in a non-linear manner, while improving air quality in neighboring cities (Zhang et al., 2022c; Zhou et al., 2018). Additionally, urban form, population densities, and ambient air pressure were found to be among the several factors that have impacts on air quality. Multi-city air quality studies still face uncertainties due to issues with remote sensing data from multiple sources, such as scale mismatches between in-situ measurements and remote sensing observations in generating gridded air quality data. For instance, Wang et al. (2021) found that using different methods to derive air pollution exposure data can result in different estimates of premature mortality changes, underscoring the importance of robust methods for estimating gridded datasets of air pollutants. Creating gridded datasets of air pollutants with high frequency and accurate spatiotemporal patterns remains a challenge due to the high heterogeneity of spatiotemporal variations of air pollutants.

3.7. Carbon budgets

Urban areas play a critical role in climate change both as the primary emitters of anthropogenic greenhouse gasses, as hotspots of vulnerability to the impacts of climate change, and as the stage where policy and action to mitigate climate change is playing out. More than 1100 cities have committed to halve carbon emissions by 2030 and reach net zero by 2050 (United Nations, 2023). As such, tracking urban carbon budgets is important both for monitoring the collective contribution of urban activities to climate change, but also for local level decision-making aimed at mitigating carbon emissions. Remote sensing on urban carbon budgets has contributed to four main areas of research: (1) measuring and mapping emissions directly, (2) monitoring the progress of mitigation strategies, (3) estimating the impact of land changes from urbanization on carbon sinks, and (4) measuring the contribution of urban vegetation to carbon sequestration. This work has relied on a diversity of sensors: multi-spectral daytime imagers onboard Sentinel, Landsat, and MODIS/VIIRS to monitor change in carbon stocks, nighttime radiometers like VIIRS-DNB and DMSP-OLS and NO_2 instruments like TROPOMI to refine the spatial distribution of emissions, and instruments that measure the vertical column density of CO_2 directly (SCIAMACHY, TANSO-FTS, GOSAT/GOSAT2, TanSat, OCO-2, and OCO-3).

The multi-city studies we reviewed on carbon budgets incorporated anywhere from 2 to 653 cities. Half of the studies used less than 27 cities, and only 4% processed more than 350 cities. The main rationale for including multiple cities was to be comprehensive – to understand collective urban carbon emissions in a particular geography (e.g., global studies, national studies, or studies that completely covered a smaller geographic scale like a province or urban agglomeration). Assessments of Chinese cities constituted the majority of the studies examined. Most of these studies aimed to be comprehensive in their scope – either capturing all of the prefecture level cities in China (of which there are currently 278), or all of the cities within a particular region or urban agglomeration [e.g., the Pearl River Delta (Cui et al., 2019) or Beijing-Tianjin-Hebei agglomeration (Chen et al., 2022)].

We found few studies that chose a sample of cities intentionally for representation. Selection of cities is often linked to having available ground-based measurements, satisfying criteria that enables a satellite algorithm to work, or having sufficient observations (Kort et al., 2012; Zheng et al., 2020). Studies with representative samples tended to be urban vegetation and carbon sequestration assessments, which focused on choosing cities in different biomes, with different topographies and climatic conditions. The second most popular schema for choosing a city sample was based on population, for example, focusing on cities with populations over a certain threshold. All of the global studies we reviewed focused on large well-known global cities or megacities.

The carbon budgets of large cities are important to understand due to their outsized role in producing global direct emissions. In 2017, 18% of all global emissions came from just 100 cities (Moran et al., 2018). However, the vast majority of urbanization is occurring in small to medium sized cities of the developing world (Zimmer et al., 2020)—so these understudied places are projected to have a growing impact on climate change, while arguably offering the least cost pathway to low-emission, climate resilient urbanization. Furthermore, secondary cities generally lack the institutional and technical capacity as well as the financial resources for climate response that are available to larger "global" cities.

Pan et al., (2021) reviewed the potential of CO_2 satellite monitoring for climate governance – an emerging critical need – and note a number of studies with multiple cities. We expect there to be an escalation in the number of multi-city studies that measure urban emissions by satellite in the near future. Satellite monitoring of urban CO_2 has been limited by the current satellites, which were designed to measure regional biospheric carbon fluxes or global atmospheric CO_2, not anthropogenic CO_2 (Nassar et al., 2017). Sensors must have high revisit frequency over the same urban area to constrain emissions estimates, particularly with clouds and urban air pollution, so the low repeat cycle of satellites like OCO-2 and GOSAT is limiting for urban monitoring. Several future satellite missions are planned that will be well-suited to monitor carbon dioxide (Pasternak et al., 2017), GHGSat-C2 (Ligori et al., 2019), and OCO-3 (Eldering et al., 2019), among others.

3.8. Green space

Urban green space refers to the vegetated urban land cover of various uses, such as street trees, parks, community gardens, sporting fields, stream banks, greenways, green roofs, and lawns, which provide essential ecosystem services to improve the quality of life for city dwellers (Wolch et al., 2014).

Mapping and analyzing urban green space can be treated either as part of a broader LULC mapping task, or an independent mission. In either way, multi-city urban green space studies have been largely driven by the research purposes of understanding the differences and similarities in the spatial patterns of vegetation fragmentation, growth or phenology, as well as the effects of urbanization on the dynamics of these patterns (e.g., Zhou et al., 2016; Ruan et al., 2019; Kowea et al., 2021). This is especially true for the Land Surface Phenology (LSP) research, where the response of plant phenology to the changing climate and rapid urbanization are highly complex. Studying its patterns over multiple, diverse cities provides a mechanistic understanding of the drivers of plant phenology in an urban setting (Zhou, 2022).

Studies of urban green space have been traditionally conducted in major cities over developed regions in the northern hemisphere (such as Europe and North America), where green space was treated as having higher economic and ecosystem service values compared to that in many developing countries (Cilliers et al., 2009; Kowe et al., 2021). However, there has been a recent trend of expanding study areas into cities of China, Southeast Asia, and South America (e.g., Nor et al., 2017; Zhou et al., 2018; Ju et al., 2022). The main criteria for city selection are relatively consistent across studies, which tend to cover mid- and large-size cities of high geographic or climate variations, as well as varying demographic and economic conditions. Climate is a particularly important criterion since it directly affects vegetation growth, species distribution, and phenology, leading to significant variation across cities.

While urban green space has long been recognized to provide a plethora of ecosystem services to support the physical and psychological wellbeing of city dwellers since the nineteenth century (Swanwick et al., 2003; Dickinson and Hobbs, 2017), most studies were based on field observations. Remote sensing provides a spatially explicit monitoring capacity of urban vegetation over broad areas, which has led to in-depth knowledge or new angles in understanding the value and role of the green space. Representative applications include studies of urban heat islands (Nastran et al., 2019), the cooling effect (Aram et al., 2019), sustainability (Badiu et al., 2016), risk of death (Bixby et al., 2015), environmental justice (Kabisch et al., 2016), biodiversity (Sultana et al., 2022), and health of children and seniors (Sikorska et al., 2020).

Urban green space as an attentive subject in remote sensing has a relatively short history starting in the 2000s. While it becomes increasingly routine to remotely capture the spatial coverage and temporal dynamics of urban green space, most of the multi-city algorithms were developed at a coarse resolution (e.g., 30 m). Such a resolution tends to overlook small-scale urban green space, which spreads across the entire urban region (e.g., street trees). When considered in their totality, a significant amount of urban vegetation is likely to be ignored in the analysis (Godwin et al., 2015; Shahtahmassebi et al., 2021). Researchers had to use spectral unmixing to extract urban vegetation fraction. While airborne LiDAR and very-high resolution sensors offer an effective means to take a fine scale look at urban green space (e.g., at individual tree level), most studies were still conducted at the local scale focusing on one single city or municipality (Kowe et al., 2021). This issue could be addressed by the increased availability of very-high resolution or hyperspectral imagery, an openly accessible field data network (e.g., tree height, species types, biomass, and infestation) across cities, and advanced cloud computing power (e.g., Google Earth Engine, Gorelick et al., 2017).

4. Multi-city studies in the special issue

This special issue aims to review and synthesize the latest cutting-edge advances in remote sensing multi-city studies. The guest editors received a total of 56 abstract submissions (for pre-approval) and 44 full manuscript submissions. Following a rigorous peer-review process, 19 papers were accepted and included in the special issue. These accepted papers are broadly focused on urban LCLU and its change (8 papers), followed by studies of urban vertical structure (4), SUHI (3), hazards (1), green space (1), surface albedo as a joint effect of urban LCLU, green space, and climate (1), and a review of multi-city remote sensing (this paper). Table 1 provides more details about these special issue papers (excluding the review paper), including the author, specific research topic, novel contribution, and the cities studied. Overall, these studies remain focused on major cities (or city clusters or metropolitan areas) in China, the U.S., and Europe, which follows the existing trend discovered in our review. Most of the studies did not explicitly explain the rationale behind choosing multiple cities, although some of them did point out key factors, such as model generalization for effective knowledge transfer (Daams et al., 2023), and the comparison of peer cities to inform urban sustainable development (Chakraborty & Stokes, 2023). The criteria for city selection were designed to meet specific research goals, which is consistent with our review findings. We also found a common strategy to boost city representation by incorporating urban regions of diverse geographic regions, sizes, and/or climatic zones. These studies provide a representative sampling of the characteristics of the multi-city studies described as part of the review.

Table 1.

List of the special issue papers, describing author, research topic, novelty, and cities studied.

Author	Research Topic	Novel Contribution	Cities Studied
Cao & Huang (2023)	Building change detection	• Reduced needs for manual labeling. • Enhanced model performance via uncertainty-aware pseudo label generation, a noise-robust network, and reducing data distribution differences between time-series images at multiple levels.	27 major cities in China
Chakraborty & Stokes (2023)	Urban change detection	• Developed a data-driven approach using neural networks to learn city-specific NTL time-series models of the expected baseline behavior. • Capable of detecting both positive/negative and gradual/abrupt changes.	11 cities across North America, Asia, and Africa
Chen P. et al. (2023)	Building height estimation	• Synergized Photogrammetry and Deep learning methods (BHEPD). • Enhanced accuracy of heights estimation, particularly for high-rise, high-density, and multi-scale buildings.	8 major cities in China
Chen T.K. et al. (2023)	Human settlement detection	• Demonstrated, for the first time, the potential of deep learning to detect	Multiple northern states of India,

		human settlements in mountains at the sub-pixel level.	and the nations of Nepal and Bhutan
Daams et al. (2023)	Metropolitan boundary mapping	• Introduced a consistent measure of metropolitan boundaries. • Highlighted the typically unobserved role that study area definition and selection may play in affecting outcomes in remote sensing studies in urban settings.	687 European metropolitan areas
Frolking et al. (2022)	Global trends of urban building volumes	• Quantified trends in urban microwave backscatter across large cities and three decades. • Analyzed the relationship of urban microwave backscatter to building volume, and to city-scale economic activity.	477 large cities across China, Europe, and the U.S.
He et al. (2023)	Sub-pixel urban land cover mapping	• Combined the learning ability of the data-driven idea with the spatial correlation modeling process. • Developed a learnable correlation based sub-pixel mapping network (LECOS).	Major cities in China
Hong et al. (2023)	Cross-city semantic segmentation	• Built a new set of multimodal remote sensing benchmark datasets (including hyperspectral, multispectral, SAR). • Developed a high-resolution domain adaptation network (HighDAN) to promote the AI model's generalization ability.	Two cross-city scenes in Germany and in China, respectively
Hu et al. (2023)	Assessments of human exposure to extreme heat	• Generated hourly human heat exposure maps at 1-m spatial resolution during heat waves and non-heat wave days. • Investigated spatiotemporal patterns and the impacts of urbanization intensity and urban morphology on heat exposure.	Three cities in the U.S.
Li B. et al. (2023)	Terrain elevation correction	• Developed an auto-refinement method for correcting the terrain elevation product of ICESat-2 in urban areas. • Mixed terrain elevation data from the strong- and weak-beam observations to ensure broad applicability.	Three cities in the U.S., the Netherlands, and New Zealand, respectively
Li L. et al. (2023)	Drivers of urban greening or browning	• Used satellite-derived enhanced vegetation index to examine the greenness trends in China for 2000–2019. • Developed a conceptual framework to differentiate between the contributions of biogeochemical and land-cover change drivers to the greenness trends.	1560 cities across China

Liu et al. (2023)	Sensitivity of SUHI intensity estimates to non-urban reference	• Provided the first test on the sensitivity of SUHI intensity trend estimate to seven methods of non-urban reference delineation. • The selection of different non-urban references significantly altered SUHI intensity.	281 Chinese cities
Ma P. et al. (2024)	Deformation estimation	• Developed a bidirectional gated recurrent unit (BiGRU) model to correct random and seasonal atmospheric delays in InSAR time series. • Mapped the first overall subsidence velocity of the Irrawaddy Delta city cluster and deformation in Myanmar.	Three city clusters in China and Myanmar
Ma X. et al. (2023)	Fine-scale building height	• Developed a generalizable approach to map large-scale distributions of building heights. • Extrapolated GEDI-derived samples discretely to the continuous building height map at the 150-m grid size.	41 cities in the Chinese Yangtze River Delta (YRD) region
Wu et al. (2024)	Surface albedo	• Generated a 30-m-resolution annual surface albedo dataset for global cities from 1986 to 2020. • Revealed an overall decreasing trend of albedo with its variance well explained by urban greening.	3037 major cities worldwide
Yang & Zhao (2023)	Patterns and drivers of SUHI seasonal hysteresis	• Identified the direction and shape of SUHI seasonal hysteresis across Chinese cities. • Urban-rural differences in evapotranspiration and surface albedo were recognized as the primary contributors.	Major Chinese urban clusters
Zhang et al. (2023)	Automatic detection of inland/seaward urban sprawl	• Developed a fully automatic algorithm for detecting urban sprawl without manually collecting training samples. • Uncovered a neglected but dramatic seaward urban sprawl process in Chinese coastal cities.	75 coastal cities in China
Zhong et al. (2023)	Global urban high-resolution land-use mapping	• Constructed a very high resolution urban land-use dataset. • Developed an automatic multi-city mapping and analysis (GAMMA) framework.	Capital cities of 193 member states of the United Nations and 34 provincial cities in China

5. Opportunities and future directions

5.1. New sensor systems for data acquisition

Urban features, such as buildings, roads, and trees, exhibit significant heterogeneity in terms of their sizes, shapes, and spatial patterns. This diversity is particularly evident in areas encompassing multiple cities, where, in addition to within-urban heterogeneity, urban planning and design are influenced by various factors such as climate, population, land cover, economic development, cultural heritage, governance, technology, and community needs. Over the past four decades, spatial resolution has remained a crucial parameter in urban remote sensing, enabling the detection and differentiation of urban features (Welch, 1982; Weng, 2012). With the rapid advancements in satellite sensor technologies, it is anticipated that sub-meter resolution satellite data will become the standard input for urban studies, allowing for the capture of fine-grained spatial variations in urban features across diverse cities. For instance, the upcoming Albedo satellite constellation is poised to provide high-resolution imagery from space at a remarkable resolution of 10 cm (Albedo Space Corporation, 2023).

When using proprietary remote sensing data, single city studies are inherently more affordable than multi-city studies. However, the growing influx of remote sensing companies entering the market is anticipated to enhance the cost-effectiveness of studying multiple cities, despite the present higher costs. By utilizing satellite constellations and harmonizing data from multiple sensor systems, it will be possible to observe cities more frequently, enabling the timely monitoring of large-scale urban development and facilitating rapid responses to support disaster recovery efforts.

In the past decade, artificial intelligence (AI) has brought fundamental changes in the field of remote sensing data processing. However, there has been a limited focus on the development of intelligent systems for data acquisition. Currently, UAS or drones are predominantly operated by human pilots who rely on experience in flight path design, knowledge of local urban environments to ensure successful data acquisition, and use one drone at a time. Consequently, drone surveys are often confined to small areas within a single city. The integration of AI holds great potential in addressing this limitation.

By leveraging existing urban environmental information, AI can facilitate automated communication among multiple drone sensors and enable the online design of optimal flight paths during data acquisition campaigns (see Fig. 4). This would enable broader coverage across multiple cities and enhance the efficiency and effectiveness of drone-based surveys.

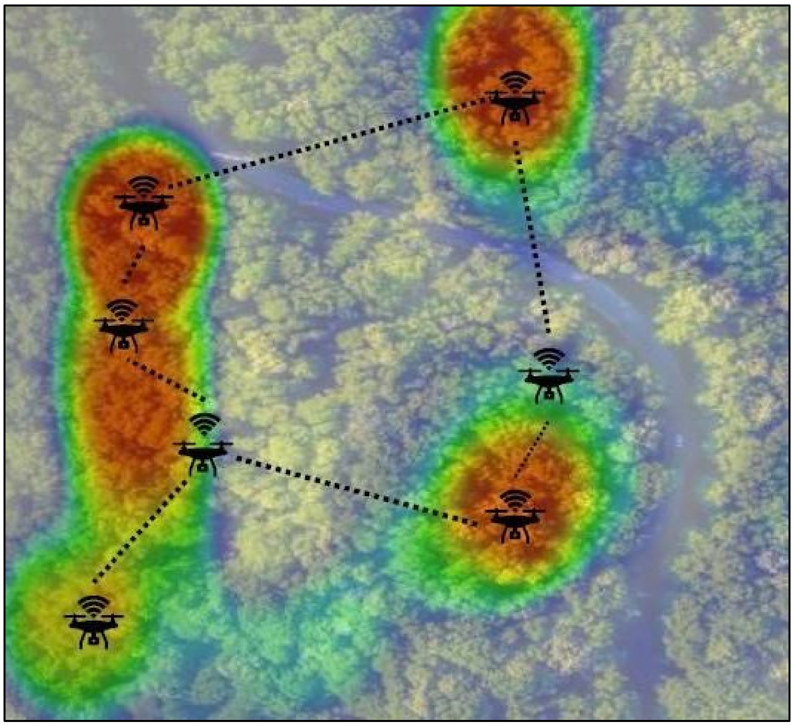

Fig. 4. Leveraging artificial intelligence and existing urban environmental information (e.g., a heat map indicating priority regions) to facilitate automated communication among drones and enable the online design of optimal flight paths during data acquisition campaigns.

5.2. Open remote sensing

Multi-city remote sensing studies have a close connection to open remote sensing. The availability of open remote sensing data, e.g., from MODIS, Landsat and Sentinel are key to the ability to undertake multi-city studies and have greatly contributed to our understanding of urban environments. Landsat in particular has provided an important advance allowing multi-city analysis at resolutions appropriate to assess urban areas over regional to global scales, now being complemented by Sentinel (Wulder et al.

2022). On a larger scale, openness is a key requirement of Big Earth Data science value-chain framework (Guo et al. 2020).

Beyond the provision of open remote sensing data, the establishment of open processing chains using open algorithms or open (or semi-open) data processing platforms are important to multi-city studies. The Global Human Settlement project supported by the European Commission is an example of a multi-city relevant open project that provides global scale spatial information related to cities based on open remote sensing. Another is the World Urban Database and Access Portal Tools (WUDAPT) project. Using an open framework, WUDAPT implements a method to implement the Local Climate Zone (LCZ) scheme defined by Stewart and Oke (2012) that classifies land areas using a number of attributes expected to influence the air temperature of the zone. WUDAPT provides an online open access LCZ generator (Demuzere et al., 2021) that uses open source earth observation data along with Google Earth Engine's random forest classifier to undertake the LCZ classification. This provides a basis for standardizing the assessment of cities at the global scale (Demuzere et al., 2022). The increasingly finer spatial resolution of urban applications, such as numerical modeling of urban climates, is now driving demand for higher spatial resolution open remote sensing data. Inputs to these models from open remote sensing, from projects such as WUDAPT, extend our ability to better understand multi-city physical processes beyond the snapshots provided by remote sensing and to developing forecasting abilities at the urban scale (e.g. Masson et al., 2020).

The sparse availability of high resolution open remote sensing and complementary/ancillary data is a critical limitation to expanding single city analyses on urban morphology and urban systems across multiple cities. For example, detailed characterization of urban morphology is provided by LiDAR, but these datasets are more variable in their openness (Heldens et al., 2019). Middel et al. (2022) identified data ownership issues as a concern. Data generated by citizens, an important addition to open remote sensing datasets that enables further analysis (Zhu et al., 2019), are often owned by private companies, and access to 3D urban morphology models for some applications can be restricted. Gomes et al. (2020), in their overview of platforms for EO data management and analysis, noted variability in the 'openness' of these platforms. Google Earth Engine for example provides an easy to use and mature system for users, but is a closed platform that cannot ensure reproducibility of analysis. Such platforms are necessitated by the large amounts of remote sensing data (Sudmanns et al., 2019). Sudmanns et al. (2022) argued for open source EO data cubes as a scalable and versatile technical solution to provide an analytical platform for big EO data and Wellmann et al. (2020) advocated for urban scale, and possibly nationally centralized, data cubes to build around the typical urban-scale geographic information system information that most cities have to more broadly integrate remote sensing data at different scales for the city. The combination of open (non-remotely sensed) data poses its own challenges (Zhu et al., 2019) that include the various – and different – scales at which open urban and open remote sensing data are collected, the potential for data sparsity to occur given the uneven collection of open urban data and biases in the open urban datasets. Ultimately, the provision of open data and processing chains will contribute to increased applications, diversification and expanded knowledge of urban systems, based on the benefits of past open data policies (Wagemann et al., 2020). Data intensive science – the 'fourth paradigm of research' – imagines knowledge discovery based on data-intensive science (Goodey et al., 2022). Remote sensing based on open data and employing tools of AI are now beginning to emerge (e.g., Corbane et al., 2021) that will directly contribute to the needs of multi-city studies.

5.3. Smart data processing and analytical systems

The efficient collection, management, storage, and analysis of remote sensing data have become increasingly vital for the development of intelligent decision systems, offering unprecedented opportunities in the field of urban studies (Liu et al., 2016). Many studies on urban remote sensing, e.g., (Hu & Xu, 2018; Liu et al., 2017; Pham et al., 2011; Sobrino et al., 2013), have predominantly concentrated on individual cities or local regions, primarily attributing to the difficulties associated with compiling and processing vast amounts of data. Nevertheless, the dynamics of a town or city are influenced by its capacity to engage and interact with other towns and cities, depending on the town or city's position within the broader settlement system, encompassing factors such as hierarchical level, specialization, and accessibility. The utilization of AI in automating the processing and analysis of remote sensing data offers significant opportunities for multi-city analyses (Zhou et al., 2020), for example, enabling capabilities in mapping urban extent or population growth at large spatiotemporal scales across cities (Gao & O'Neill, 2020; Li et al., 2018; Wang et al., 2022a), and facilitating the exploration of intra and inter urban environmental issues, e.g., urban heat island, greenhouse gas emissions, and air pollution (Chakraborty et al., 2019; Xu et al., 2019).

The successful application of advanced technologies such as AI and ML algorithms has contributed to the increasing importance of remote sensing in addressing the challenges posed by rapid urbanization and growing populations (Youssef et al., 2020). However, the integration of AI/ML and geospatial data into urban studies faces challenges associated with data collection and algorithmic complexity in comparison to single-city studies. The effectiveness of these applications is highly dependent on the size and quality of the data used, as well as the careful selection of appropriate models. Although remote sensing data offers large spatial coverage and high availability, it may not always possess the required level of accuracy for specific uses (Tekouabou et al., 2022). Therefore, it is crucial to prioritize the use of high-quality remote sensing data to achieve optimal performance. Alternatively, integrating remote sensing data with other sources, such as open city and mobile device data, can enhance the accuracy and overall quality of existing datasets in multi-city studies. In addition to data quality, the future of AI/ML applications in multi-city studies will depend on the expansion and diversification of available models, as well as their scalability to handle the increasing volume of urban data being collected.

The rapid progress in data collection and storage capabilities, along with advancements in machine computational power, have paved the way for the development of new algorithms capable of processing large remote sensing data for diverse urban applications including multi-city studies (Liu et al., 2017; Wang & Biljecki, 2022). It is worth noting that these algorithms can be more complex compared to those developed for a single city, and their complexity can be magnified by the substantial volumes of urban data being collected at present. As a result, the implementation and deployment of AI/ML for real-time applications, such as multi-city energy use monitoring, poses challenges due to the significant computational capabilities required (Jordan & Mitchell, 2015). To address such challenges, one potential solution is to integrate AI methods into hosted computing platforms, such as Google Earth Engine, a cloud computing platform specifically designed for storing and processing petabyte scale datasets (Yang et al., 2022).

5.4. Integration with knowledge from other professional domains to create a new urban science/guidance for choosing city samples

In recent years, both the National Academy of Sciences (National Academies Press, 2016) and the U.S. National Science Foundation (Advisory Committee for Environmental Research and Education, 2018) have called for a new use-inspired discipline, called urban sustainability science (USS), to develop the knowledge needed to guide urban development towards more sustainable pathways. USS inherently involves convergence research (Acuto et al., 2018; Advisory Committee for Environmental Research and Education, 2018; Lobo et al., 2019) – integrating urban disciplines and working across scales to identify interactions, thresholds, trade-offs, and feedbacks between urban socio-economic systems and environment.

Multi-city remote sensing studies are core to the vision of USS. In particular, multi-city studies are needed to (i) create a new theory that transcends single urban areas (Lobo et al., 2019), (ii) examine urban areas collectively as social, economic, infrastructural, and spatial complex systems that comply with scaling laws across local, city, regional, and national spatial scales (Bettencourt et al., 2013), and engage institutional policy that is shaping urbanization processes at multiple scales to limit unintended consequences (Seto et al., 2017; Acuto et al., 2018), (iii) identify groups of "peer cities" that may benefit from similar sustainability strategies to scale up action effectively (Advisory Committee for Environmental Research and Education, 2018), and (iv) enable the examination of planetary impacts of urbanization in aggregate, e.g., species extinction, emissions production, agricultural land loss (Seto et al., 2017). Therefore, USS is both a motivation for more multi-city remote sensing studies and an opportunity for these studies to be actionable and to point the way to sustainable urban futures.

To build up an USS, multi-city remote sensing studies must rely on intentional sampling schema, that allow a study to make inferences about larger groups of urban areas, and to get insight about the fundamental character of urban processes. The generalizability and representativeness of the results of a study are directly dependent on the sample (size and distribution) of urban areas selected for data collection. Though stratified, systematic, cluster, and random samples are often used in the validation of remote sensing (Congalton and Green, 2019), they are less often explicitly used at the onset of a study, in the selection of where to gather observations. One of remote sensing's key advantages over ground-based surveys of urban change is the ability to collect data, repetitively, and with large area coverage (Forster, 1985). As such, urban remote sensing is not limited to the largest and wealthiest megacities, where ground data is already extensive, but instead can help build a science that captures the processes changing secondary cities and those in the Global South as well. Despite the potential, convenience sampling – a non-probability sampling technique where researchers choose their urban sample based on the accessibility of data or funding or because of a priori familiarity – remains a common practice in urban remote sensing studies, and limits the growth of USS.

6. Conclusion

Remote sensing of urban environments is undergoing an important transition from a focus on single cities to studies that encompass multiple cities. Our project undertook a comprehensive analysis of eight key areas, namely LULC and its changes, urban vertical structure, urban heat islands, hazards, energy use and emissions, air quality, carbon budgets, and green spaces (Figure 5). The primary objective of our project was to gain insights into the underlying rationale behind conducting multi-city studies, the criteria employed for city selection, the societal applications thereof, and the potential future prospects for expanding the scope of multi-city remote sensing assessments.

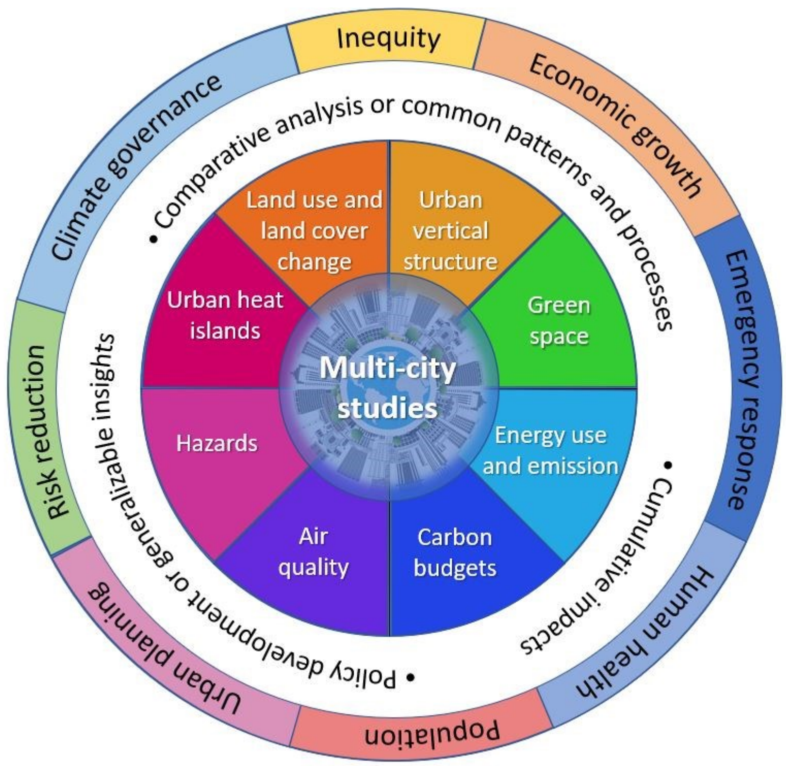

Fig. 5. Understanding urban environmental/physical processes as a rationale that is often part of the chain of working towards the greater societal impacts on the outer ring of the diagram in multi-city studies.

The rationale behind conducting multi-city studies was found to be relevant to three key factors. First, it pertains to the generalizability or representativity of the proposed study, ensuring its applicability across diverse urban environments. Second, it addresses the need to assess patterns and underlying mechanisms of urban system functioning across multiple cities. Third, it takes into consideration the constraints posed by data availability, quality, and comparability of field observations when focusing solely on a single city. Our review detects a notable bias towards assessments of large cities, with particular geographical emphasis on cities located in China, Europe, and North America. The selection of cities was contingent upon specific research goals, such as regional or global significance, rapid urban expansion, physiographic settings, city politics, socioeconomics, culture, biomes, topography, and climatic conditions. However, it is worth noting that multi-city studies were often implicit rather than explicit. For instance, assessments related to hazards were driven by the scale of the hazard itself, incorporating multiple cities as a result, rather than intentionally selecting multiple cities for study. The terms "diversity" and "representativity" frequently appeared in the study area section of multi-city studies. Nevertheless, specific criteria defining diversity, representativity, or the required number of cities to ensure sufficiency have yet to be established.

Despite the existing challenges, the understanding of urban environmental/physical processes gained from multi-city studies has proven to be immensely beneficial to society. This knowledge informs various aspects, including economic growth, urban inequity, climate governance, risk reduction, urban planning, population dynamics, human health, and emergency response, ultimately contributing to sustainable development and management (Figure 5). In particular, the reviewed eight key fields of multi-city remote sensing are not mutually exclusive. When collectively considered (e.g., integrating LCLU change, urban vertical structure, and urban hazards), they can illuminate new opportunities in evidence-based urban research and practices by capturing accurate, multifaceted, and interactive urban characteristics or functions. Furthermore, several opportunities have arisen for multi-city studies. These include the availability of new sensor systems that facilitate efficient acquisition of high-quality data, the utilization of open remote sensing, encompassing open data and processing chains, to expand the range of applications, the diversification and enhancement of knowledge pertaining to urban systems, and the development of smart data processing and analytical systems capable of handling extensive remote sensing data from diverse urban regions. It is important to note that multi-city remote sensing studies are core to the vision of a new urban science – urban sustainability science (USS). To build up an USS, multi-city remote sensing must develop an intentional city sampling schema through the integration of knowledge from other professional domains.

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